Use of *a Priori* Parameter-Estimation Methods to Constrain Calibration of Distributed-Parameter Models

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Over-parameterization, ungauged basins, and the assessment of the impact of land-use and climate change are a few of the problems that limit the use of calibration techniques for distributed-parameter models. One approach to addressing these problems is the use of *a priori* parameter-estimation procedures to minimizing the number of parameters to be calibrated, or to obtain parameter values where calibration is not possible. A set of modeling and analytical tools is being developed using the US Geological Survey's Modular Modeling System to facilitate the development and evaluation of objective *a priori* methods. Initial testing of these tools was conducted on basins in the Rocky, Sierra-Nevada, and Cascade Mountain Regions of the United States. *a priori* parameter estimates were made for the USGS distributed-parameter model PRMS using available digital datasets of terrain, soils, vegetation type and density, and climatological data. Only the Rocky Mountain basin had an acceptable uncalibrated performance. Model performance for all basins improved as the parameters calibrated were increased incrementally from none, to those affecting the water balance, then hydrograph timing, and then all soils and vegetation related parameters. Problems were identified in the use of the forest-density dataset as a surrogate for forest cover density. A full evaluation of the soils dataset for determining available water-holding capacity was not possible due to the insensitivity of the model to this parameter in these snowmelt basins. Key issues in *a priori* parameter estimation for this limited application were identified to include regional climatic and physiographic differences, dataset limitations, and selection of measures of parameter and model performance. These will be addressed in an expanded research effort using tens of basins in different climatic and physiographic regions of the United States and the world.

INTRODUCTION

A major difficulty in the use of distributed-parameter models is the general lack of objective methods to estimate the values of distributed parameters. Calibration techniques are typically used to compensate for various sources of uncertainty in these estimates. However, the transferability of calibrated results to other basins is often an issue due to the over-parameterization of many distributed-parameter models and the incorporation of model and data errors in fitted parameter values. The application of calibration techniques to problems such as ungauged basins, or assessing the impact of land-use and climate change, is further limited because there are typically no measures of system response against which to calibrate. Estimating parameters where calibration is not possible, and addressing the over-parameterization problem by minimizing the number of parameters to be fitted, requires the development of methods that relate parameter values to measurable climatic and basin characteristics.

The development of methodologies to relate selected model parameters to climatic and basin characteristics has been conducted by a number of disciplines in the field of hydrology.

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Studies at the point and plot scale have typically been used to define these relations. For example, in the area of soil physics, Rawls and Brackensiek (1983) developed a methodology to estimate soil water-holding capacities and Green-Ampt infiltration-model parameters using soil-texture information. More recent work by Schaap et al. (1998) has focused on the use of soil-properties data to develop pedotransfer functions for the estimation of water-retention and hydraulic properties. Similar efforts are being conducted in other areas with regard to a variety of hydrologic and climatic processes (e.g. Koren, et al., this volume). However, the application and evaluation of such techniques over larger areas have been limited. The ability to define the most appropriate parameter-estimation methods for use with different models in different climatic and physiographic regions, and to specify the robustness and reliability of these methods and their associated datasets, are major knowledge gaps.

The increasing availability of high-resolution spatial and temporal datasets of climatic and basin characteristics now provides the opportunity to investigate and develop *a priori* estimation procedures for distributed model parameters. To facilitate the development, testing, and evaluation of *a priori* parameter-estimation methods for a variety of models and datasets, a set of tools is being developed using the US Geological Survey's Modular Modeling System (MMS) (Leavesley et al., 1996; 2002). MMS is an integrated system of computer software that provides a common framework for multidisciplinary research and operational efforts to develop, evaluate, and apply a wide range of modeling capabilities and analytical tools. The long-term objectives of this research effort are to (1) develop and evaluate objective *a priori* parameter-estimation methods using available spatial and temporal datasets, and (2) evaluate and identify the most robust process-model conceptualizations and parameters for both uncalibrated and calibrated applications in different climatic and physiographic regions.

This paper focuses on the first objective. It describes the initial development and testing of a set of methodologies and tools for use with available digital datasets in three snowmelt regions of the western United States. The effort was limited to applications in mountainous regions where snow accumulation and melt processes dominate the hydrological cycle. This provided a focus on common hydrologic processes but in different climatic regimes. As the first step in a larger, more comprehensive effort, the study was further limited to only one model and a single basin in each of the three snowmelt regions. The next steps in this research will be the application of the tools and knowledge developed in this study to ten's of basins in the study regions and the development of a fully integrated set of models, methods, and tools to address both research objectives given above.

STUDY BASINS

Snow-dominated, mountain basins were chosen in the Rocky, Sierra Nevada, and Cascade Mountain Ranges in the United States. The basins selected (Fig. 1) were (1) the Animas River basin, which has a drainage area of 1820 km^2, and elevation that ranges from approximately 2000 to 4000m; (2) the East Fork of the Carson River basin (hereafter referred to as the Carson River basin), which has a drainage area of 920 km^2 and elevations that range from approximately 1600 to 3000m; and (3) the Cle Elum River basin, which has a drainage area of 526 km^2 and elevations that range from 600 to 2000m. Vegetation on all the basins is predominantly coniferous forest with a mix of alpine tundra and bare rock occurring on areas above timberline.

MODEL

The USGS Precipitation-Runoff Modeling System (PRMS) (Leavesley et al., 1983; Leavesley and Stannard, 1995) is a distributed-parameter, physical-process watershed model. Distributed-parameter capabilities are provided by partitioning a watershed into units, using characteristics such as slope, aspect, elevation, vegetation type, soil type, and precipitation distribution. Each unit is assumed to be homogeneous with respect to its hydrologic response and to the characteristics listed above. Each unit is termed a hydrologic response unit (HRU). A water balance and an energy balance are computed daily for each HRU. The sum of the

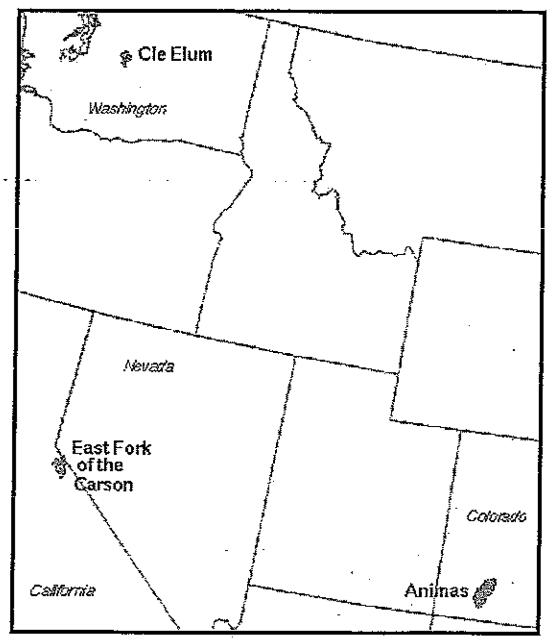

Figure 1. Study basin locations.

responses of all HRUs, weighted on a unit- area basis, produces the daily watershed response.

Snow is the major form of precipitation in the Animas, Carson, and Cle Elum River basins, and the major source of streamflow. The snow components of PRMS simulate the accumulation and depletion of a snowpack on each HRU. A snowpack is maintained and modified both as a water reservoir and as a dynamic heat reservoir. A water balance is computed each day and an energy balance is computed for two 12-hr periods each day. The energy-balance computations include estimates of net shortwave and longwave radiation, the heat content of precipitation, and approximations of convection and condensation terms.

PRMS uses daily inputs of solar radiation and the variables precipitation (PRCP), maximum air temperature (TMAX), and minimum air temperature (TMIN). Solar radiation was distributed to each HRU as a function of HRU slope and aspect. Solar radiation data were not available on a daily basis and so were computed using existing algorithms in PRMS. Estimates of daily shortwave radiation received on a horizontal surface were computed using air temperature, precipitation, and potential solar radiation. A list of PRMS parameters referred to in this paper and their definitions are provided in Table 1.

TOOLS

The GIS Weasel

The GIS Weasel is a geographic information system (GIS) interface for applying tools to delineate, characterize, and parameterize topographical, hydrological, and biological basin features for use in a variety of lumped- and distributed-modeling approaches. It is composed of Workstation ArcInfo (ESRI, 1992) GIS software, C language programs, and shell scripts.

Parameter-estimation methods are implemented using ARC Macro Language (AML) functions applied to available digital datasets. A library of parameter-estimation methods is maintained in a similar fashion to the library of process modules in MMS. For a given model, a recipe file of AML functions can be created and executed to estimate a selected set of spatial parameters. This recipe file can also be modified to change the parameter-estimation method associated with a selected parameter, thus enabling the evaluation of alternative parameter-estimation methods.

Table 1. Definition of selected PRMS parameters.

Group	Parameter	Definition
GIS Weasel	covden_win	Winter vegetation cover density for the major vegetation type on an HRU
	jh_coef_hru	Air temperature coefficient used in Jensen-Haise potential evapotranspiration computations for each HRU.
	rad_trncf	Transmission coefficient for short-wave radiation through the winter vegetation canopy
	soil_moist_max	Maximum available water holding capacity of soil profile
Meteorological	adjmix_rain	Monthly factor to adjust rain proportion in a mixed rain/snow event
	bias	Precipitation adjustment factor to account for gage catch efficiency and other sources of measurement error
	tmax_allrain	Maximum daily temperature above which all precipitation is assumed to be rain
	tmax_allsnow	Maximum daily temperature equal to or below which all precipitation is assumed to be snow
Runoff Timing	emis_noppt	Average emissivity of air on days without precipitation
	gwflow_coef	Groundwater reservoir routing coefficient
	soil2gw_max	Amount of the soil water excess for an HRU that is routed directly to the associated ground-water reservoir
	ssrcoef_sq	Non-linear subsurface -reservoir routing coefficient

XYZ Precipitation and Temperature Distribution

Recent research has resulted in the development of a new distribution methodology for daily values of PRCP, TMAX, and TMIN (Hay et al., 2000a,b). Significant geographic factors affecting the spatial distribution of PRCP, TMAX, and TMIN within a river basin are latitude (x), longitude (y), and elevation (z). Multiple linear regression (MLR) equations are developed for each dependent climate variable (PRCP, TMAX, TMIN) using the independent variables of x, y, and z from available climate stations. The general form of the MLR equation for precipitation at a given HRU is

$$PRCP_{(HRU)} = b_0 + b_1\, x_{(HRU)} + b_2\, y_{(HRU)} + b_3\, z_{(HRU)} \quad . \ (1)$$

The resulting fit from equation 1 describes a plane in three-dimensional space with slopes b_1, b_2, and b_3 intersecting the PRCP axis at b_0. Similar equations are used for TMAX and TMIN. Use of the station x and y coordinates in the MLR provides information on the local-scale influences on the climate variables that are not related to elevation (for example, the distance to a topographic barrier). To account for seasonal climate variations, MLR equations are developed for each month using mean values of PRCP, TMAX, and TMIN (dependent variables) and station x, y, and z (independent variables) from a set of stations selected from regional National Weather Service and Snow Telemetry (SNOTEL) stations that fall within and outside the selected basins. The monthly MLRs are computed to determine the regression surface that describes the spatial relations between the monthly dependent variables and the independent variables. Note that for each month the best MLR relation does not always include all the independent variables.

Estimates of daily PRCP, TMAX, and TMIN for each HRU are computed using the following procedure: (1) mean daily values of PRCP (TMAX and TMIN) and corresponding mean x, y, and z values from a selected station set (described in the Exhaustive Search analysis below) are used with the slopes of the monthly MLRs to compute a unique b_0 for that day and (2) the MLR equation is then solved using the x, y, and z values of the HRUs.

The regional MLR equations, typically developed for areas thousands to tens-of-thousands of square kilometers in size, may under- or over-estimate the mean precipitation (or temperature) in smaller basins typically used for hydrologic simulations. These smaller basins often range in size from a few hundred to a few thousand square kilometers. Also, measurement errors associated with precipitation, particularly precipitation gage under-catch of snow, may lead to significant errors in hydrologic simulations. To address these issues, an Exhaustive Search (ES) analysis is used to (1) determine the optimal precipitation- and temperature-station sets to anchor the xyz distribution methodology; (2) provide an estimate of bias associated with the selected precipitation stations; and (3) define a separate precipitation-station set to determine daily precipitation frequency.

Precipitation and temperature stations are selected independently since the best precipitation station choice generally differs from the best choice for temperature distribution in a basin. For every combination of these precipitation- and temperature-station sets, a precipitation bias and a station set to indicate precipitation frequency are also tested. The range of the bias correction is from 0 to 50 percent and the correction is applied only to snowfall events. The correction actually compensates for the net effect of a number of biases related to precipitation measurement, such as gauge undercatch, gage location, and/or lack of gauges at high elevation. It may also correct for other sources of bias in PRMS.

The ES analysis is run to test all single stations and possible combinations of two, three, and four station groups comprising the xyz-station sets. For each ES analysis, the best station sets for temperature and precipitation, along with an associated precipitation bias and frequency, are determined by comparing the sum of the absolute value of the difference between measured and simulated runoff. The ES analysis ends when the sum of the absolute errors associated with the above combinations shows no significant improvement from one station group to the next.

Analysis Tools

Optimization and sensitivity analysis tools are provided in MMS to analyze model parameters and evaluate the extent to which uncertainty in model parameters affects uncertainty in simulation results. Two optimization procedures are available to fit user-selected parameters. One is the Rosenbrock technique (Rosenbrock, 1960), as it is implemented in PRMS. The second is a hyper-tunnel method (Restrepo and Bras, 1982).

Several methods for parameter sensitivity analysis are also provided. One is the method described in the PRMS user's manual (Leavesley et al., 1983), which allows the evaluation of a variety of measures including relative parameter sensitivity, error propagation, and parameter correlation. A second method evaluates the sensitivity of any pair of parameters and develops the objective function surface for a selected range of these two parameters. To address the question of parameter uncertainty, a Monte Carlo procedure is available to evaluate alternative combinations of model parameters.

The basic measures of model and parameter performance used in this study were the comparisons of measured to simulated daily streamflows. One measure was expressed in terms of the sum of the absolute values of the differences between measured and simulated daily streamflow. This measure was used as the objective function in all model calibrations and was used for comparison of individual parameter sensitivity and performance. A second measure was the Nash-Sutcliffe coefficient of efficiency (CE) (Nash and Sutcliffe, 1970). It was used as a measure of model performance for alternative parameter sets.

METHODOLOGY

Parameter Estimation

PRMS HRUs were delineated and characterized using the GIS Weasel. The Animas, Carson, and Cle Elum River basins were divided into 121, 96, and 124 HRUs, respectively. Spatially distributed topographic, vegetation, and soils parameters on each HRU were estimated using available digital datasets. The datasets used were: (1) USGS 3-arc second digital elevation models (DEMs); (2) 1-km gridded version of the State Soils Geographic (STATSGO) soils data (U.S. Department of Agriculture, 1994); (3) Forest Service 1-km gridded vegetation type and forest-density data (U.S. Department of Agriculture, 1992): and the USGS GIRAS land-use/land-cover gridded coverage. A composite of GIRAS Land Cover and the Forest Type Groups was created. In this composite, the GIRAS data was only used where the Forest Type Group data described "non-forest". The resulting Land Cover dataset has a total of 44 classes.

Topographic parameters such as elevation, slope, and aspect were computed for each HRU using the USGS 3-arc second DEM. Elevation was calculated as the median of the distribution of the DEM grid-cell elevations. Slope was calculated as the mean of the distribution of the grid-cell slopes. Grid-cell aspect values were reclassified into one of eight aspect classes that represent the eight cardinal points of the compass. HRU aspect was calculated as the aspect class having the dominant number of grid cells.

The vegetation type and density datasets were used to estimate vegetation-type and vegetation-cover-density parameters on each HRU, as well as the associated parameters of interception-storage capacity and the transmission coefficient for solar radiation. HRU vegetation type was reclassified into one of four classes defined as forest, shrub, grass, and bare. HRU vegetation type was then determined as the dominant reclassified vegetation type in an HRU. Vegetation cover density was defined as the percentage of the area of the HRU covered by the dominant vegetation type canopy. For forest vegetation types, the canopy density was assumed to be equal to the mean of the forest-density values for the forest types found in the HRU, expressed as a percentage of the entire HRU area. For example, an HRU with 60 percent of its area in forest having a mean forest density of 50 percent would have a vegetation cover density of 30 percent.

Interception-storage capacity was calculated by multiplying the computed HRU vegetation cover density times the average depth of precipitation storage per unit area of the cover type. A table of interception-storage-capacity values for all vegetation types was created using values from the literature. For deciduous vegetation types, cover density and its associated interception-storage capacity were calculated for two periods, one with and one without leaves. The transmission coefficient was calculated using the "cover density - transmission coefficient" relation provided in the PRMS user's manual (Leavesley et al., 1983). For deciduous vegetation, the cover density for the period without leaves was used in this computation.

Soil type in PRMS is categorized as sand, loam, or clay, and was calculated for each HRU using the soil texture data in the STATSGO soil dataset. Soil type was calculated as the dominant soil type on the HRU. The available water-holding capacity of the soil on each HRU is a function of the water-holding characteristics of the soil and the average rooting depth of the dominant vegetation. Calculation began with the identification of the dominant vegetation type. Average rooting depth for each vegetation type was estimated from the literature and a table of rooting-depth values was linked to the vegetation-type dataset. Available water-holding capacity values in the STATSGO dataset were processed to provide an average water-holding capacity value per unit depth of soil. This value was multiplied times the average rooting depth of the HRU vegetation type to calculate the HRU water-holding capacity.

Climate-related parameters were estimated using daily data obtained from the National Weather Service and the SNOTEL data network. Precipitation- and temperature-distribution relations were computed using the xyz methodology. A threshold temperature parameter (tmax_allsnow) is used to determine precipitation form (rain, snow, or a combination of both). The estimate of tmax_allsnow was based on the assumptions that a precipitation event will have a cloud base 305 m above the ground and that a temperature at the cloud base of 0° C will produce snow. The 0° C cloud-base temperature was assumed to provide a near-surface air temperature of 1.7° C for tmax_allsnow.

PRMS parameters related to the partitioning of water among processes related to surface, subsurface, and groundwater flow, as well as all remaining parameters, were estimated from the results of other model applications in these mountainous regions and were provided as a common set for all the basins.

Parameter Evaluation

Evaluation of the *a priori* parameter-estimation methods and their use in constraining parameter calibration was conducted by examining model performance at four levels of parameter fitting. At the first level, the model was run using all estimated parameters. No calibration was conducted. HRU and meteorological parameters were estimated using the GIS Weasel and the regional MLR relations of the xyz methodology. The subset of precipitation and temperature stations used consisted of all stations within or immediately adjacent to the modeled basin. No exhaustive search was conducted.

The second level focused on the calibration of those parameters related to obtaining reasonable monthly and annual water-balances. The parameters fitted were those controlling the magnitude and distribution of precipitation and potential evapotranspiration (PET). PET was computed using a modified Jensen-Haise method (Jensen et al., 1969) with a parameter value that was varied by month. The monthly PET parameter values were calibrated to monthly estimates of PET for each region based on values obtained from the literature. Then the exhaustive search was applied in the xyz method to determine the optimal station set, bias correction, and precipitation frequency station set.

At the third level, the fitted values obtained at level two were retained and the additional parameters that affect the timing of streamflow were optimized. These included parameters affecting precipitation form, snowmelt rates, and the rates and timing of surface, subsurface, and groundwater flow processes.

At the fourth level, the fitted values obtained at level three were retained and the most sensitive spatial and non-spatial PRMS parameters were calibrated. This included several of the parameters estimated using the GIS Weasel. Level 4 was considered comparable to a full model calibration of all sensitive parameters.

With the exception of the xyz methodology, all parameter calibrations were conducted using the Rosenbrock optimization technique. The procedure used to fit distributed parameters was to adjust all values of a specific parameter simultaneously. The assumption was made that all the values of a distributed parameter were correct relative to each other and to their spatial location. The mean value of the parameter and the deviation from the mean for each HRU was computed. The mean was then adjusted and the deviations were used to recompute the individual HRU values. In the recomputation procedure, the HRU values can be increased or decreased by the same magnitude or by the same percentage of their initial value. An upper and lower bound were specified for each parameter, and individual HRU values were reset to the boundary value if they exceeded the specified bound.

Meteorological and streamflow time-series data were available for the period 1978-1996 in the Animas and Carson basins and 1978-1994 in the Cle Elum basin. Parameter calibration was conducted using the period 1978-1988 and all analyses of parameter sensitivity and model performance were conducted using the period 1989 to the end of the record or selected years within this period.

RESULTS

Parameter Sensitivity

A first step in the evaluation of parameter-estimation methods was to determine if the model had any sensitivity to the parameters being estimated. Parameter sensitivities were determined using the PRMS sensitivity analysis procedures. For comparative purposes the parameters were grouped into the general categories of (1) GIS Weasel computed, (2) meteorological process, and (3) runoff timing process. A selection of the most sensitive parameters in each group is shown in Table 2.

Comparing differences among the parameter groups for all basins showed that the meteorological parameters, in most cases, were about an order of magnitude more sensitive than those in the other two groups. Tmax_allsnow is a scalar value but was applied to each HRU and thus affected the spatial distribution of rain and snow through the effect of the temperature-distribution relations determined using the xyz-method.

Differences among the basins within parameter groups reflected the differences in the climatic and physiographic characteristics of the three mountain regions. The most sensitive GIS Weasel estimated parameters were (1) winter cover density (covden_win) and solar radiation transmission coefficient (rad_trncf) which affect the snowpack energy balance relations, and (2) the Jensen Haise HRU ET coefficient (jh_coef_hru) and available soil-water storage (soil_moist_max) which affect the water-balance relations. The higher sensitivity of rad_trncf in the Animas basin reflects the somewhat larger effect of shortwave radiation on the snowpack energy balance in the Rocky Mountains as compared to the Sierra Nevada and Cascade ranges. The most sensitive parameter in the meteorological group in all basins was tmax_allsnow, which delineates precipitation form between snow and rain. It was most sensitive in the Carson and Cle Elum basins where rain-snow combinations and rain-on-snow events are much more common than in the Animas basin.

The most sensitive runoff-timing parameters were the emissivity term in the longwave energy equation (emis_noppt) and the daily flux rate of water movement

Table 2. Percent change in model standard error for a 10 percent increase in selected parameter values.

Group	Parameter	Animas	E Fk Carson	Cle Elum
GIS Weasel	covden_win	.02	1.01	.02
	jh_coef_hru	.58	.28	.07
	rad_trncf	2.66	.82	.17
	soil_moist_max	.41	.15	.05
Meteorological	adjmix_rain	2.80	.95	.39
	bias	.61	.02	.01
	tmax_allrain	7.31	2.13	.02
	tmax_allsnow	8.51	30.45	21.67
Runoff Timing	emis_noppt	.78	3.14	.59
	gwflow_coef	.09	.18	.01
	soil2gw_max	.63	.38	.05
	ssrcoef_sq	.05	.09	.10

from the soil zone to the ground-water reservoir (soil2gw_max). The emis_noppt parameter affects the longwave energy balance computation for days with no precipitation. Soil2gw_max affects the distribution of runoff between more rapid subsurface and slower ground-water flow sources. Comparing the sensitivity of rad_trncf to emis_noppt within each basin indicates the relative effects of shortwave and longwave energy on the total energy balance for snowmelt computations in each basin. Rad_trncf is more sensitive than emis_noppt in the Animas basin but less sensitive in the Cle Elum basin, which is again indicative of a greater effect of shortwave energy in the Animas basin. The smaller sensitivity of rad_trncf in the Carson basin may be anomalous and is related to a problem of the underestimation of rad_trncf discussed in the next section.

Uncalibrated Parameters

Evaluation of the performance of selected *a priori* parameter estimates was conducted using a Monte Carlo analysis procedure. A test case was constructed to evaluate a selected set of sensitive parameters that were estimated from the spatial and climatic datasets. One thousand model runs were made using parameter sets with randomly generated values for the four parameters estimated by the GIS Weasel (Table 2) and the tmax_allsnow and the bias parameters. The results for the rad_trncf, soil_moist_max, and tmax_allsnow parameters on each basin are shown as dotty plots in Figure 2. These plots reflect the concept of equifinality where a number of different parameter sets may be suitable for reproducing observed basin streamflow (Beven and Freer, 2001). The arrows indicate the dots that represent the uncalibrated model parameter set and objective function values of the initial uncalibrated run. For a distributed parameter, the x-axis value is the mean of all HRU values weighted by HRU area. The objective-function values for the uncalibrated runs are larger than the objective-function values for the best-fit runs by about 45 percent in the Animas basin, 85 percent in the Carson basin, and 30 percent in the Cle Elum basin.

The parameter sets containing the best-fit values for rad_trncf were reasonably well constrained on the Animas and Carson basins but less so on the Cle Elum. This reflects in part the sensitivity of each basin to shortwave energy input. The mean of the *a priori* estimate of rad_trncf was overestimated in the Animas basin and underestimated in the Carson basin but had a value with a less clearly defined error in the Cle Elum basin. The higher estimate of rad_trncf in the Animas basin produced an overestimate of shortwave energy available for snowmelt while the lower estimate in the Carson and Cle Elum produced an underestimate of shortwave energy available for snowmelt.

The *a priori* estimates of rad_trncf were computed using the HRU winter vegetation cover densities computed from the forest-density dataset. The estimated mean value of the winter cover-density parameter covden_win was about 35 percent in the Animas basin and about 71 percent in the Carson and Cle Elum basins. The mean value of 71 percent for covden_win in the Carson basin appeared high. An examination of the forest density dataset for the Carson basin showed a large number of grid cells with the value of 100 percent forest density. The forest density values were based on the coregistration of Advanced Very High Resolution Radiometry (AVHRR) data and Landsat Thematic Mapper (TM) and on regression analysis of sta-

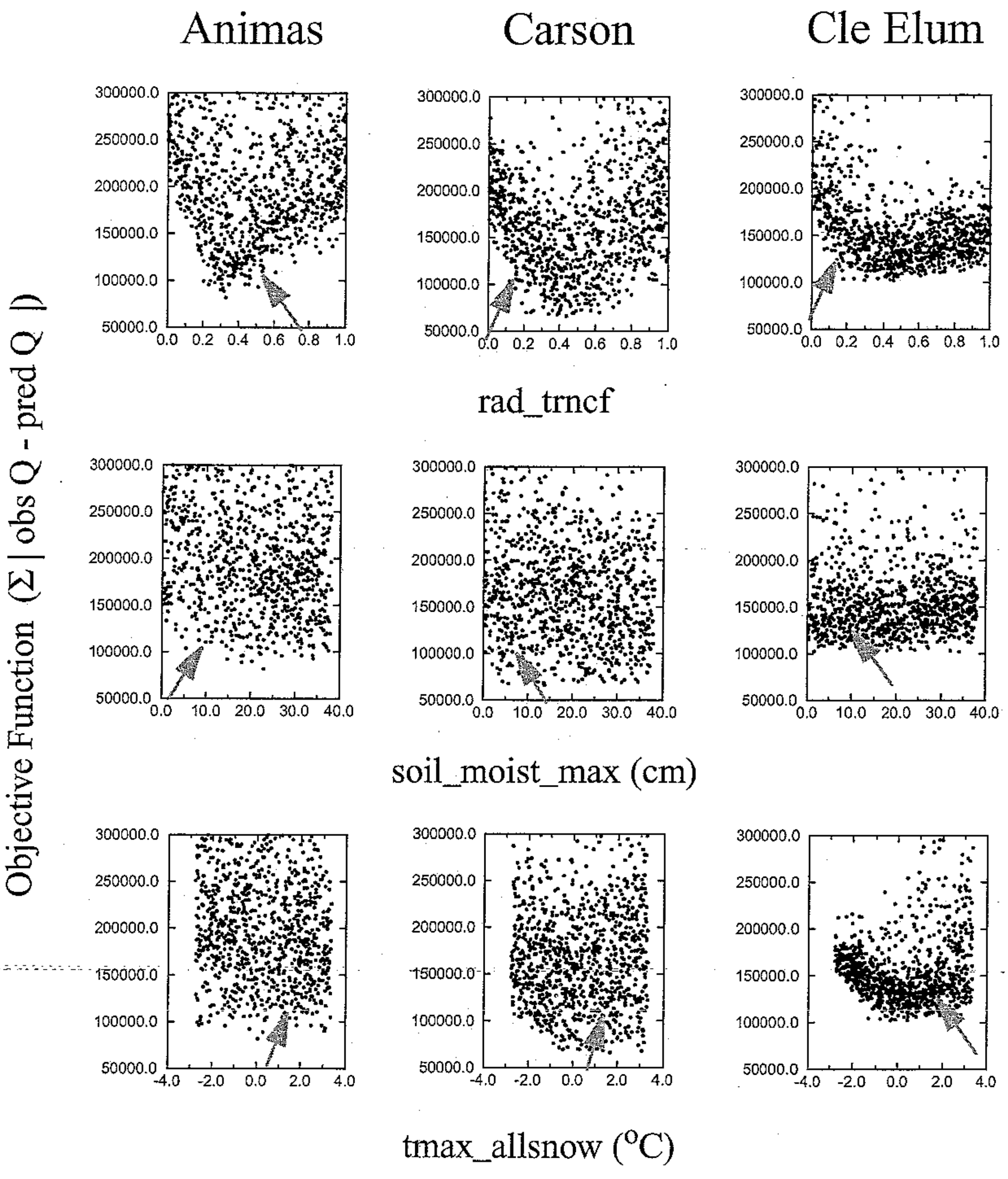

Figure 2. Monte Carlo analyses for the parameters rad_trncf, soil_moist_max, and tmax_allsnow on the Animas, Carson, and Cle Elum basins. (Arrows indicate uncalibrated parameter set values and results.)

tistical relations between the two data types (Zhu, 1994). The forest density was the percentage of forested TM cells within one AVHRR cell. There were about 1,225 TM cells in an AVHRR cell and a TM cell was considered forested if it contained a classified forest type.

Thus, 100 percent forest density from the dataset does not necessarily mean 100 percent cover of the land surface, only that 100 percent of the TM cells had some forest cover. However, covden_win is defined as one minus the percentage of the sky visible from the land or snow surface. A value of 100 percent forest cover effectively eliminates shortwave energy from the snowpack energy-balance computation. The forest-density dataset was used as an index of covden_win in this application and some adjustment for the difference in interpretation will be needed to better estimate covden_win and rad_trncf.

The soil_moist_max parameter was computed from the STATSGO soils dataset. It shows a much larger degree of uncertainty when compared to the other two parameters shown (Figure 2). This reflects the fact that in the snowmelt regions selected, the soil typically remains at or near field capacity during most or all of the snowmelt-runoff period and thus its storage capacity has only a small effect on streamflow. The snowmelt period is the major source of the annual streamflow in these basins. Consequently, the value of the STATSGO dataset for estimating soil_moist_max cannot be fully evaluated in these basins.

The relative insensitivity of tmax_allsnow in the Animas basin reflects the fact that there are few winter rain or rain-snow mixed events and that most snow events occur at temperatures well below 1.7° C. In the Carson and Cle Elum basins, winter rain and rain-snow mixed events are more common and the threshold effect of tmax_allsnow is more evident. The large increase in the objective function at tmax_allsnow values less than about 0° C results from the associated increase in the proportion of rain versus snow. This response provides some confidence that the model responds correctly to physically unrealistic values of tmax_allsnow. Smaller increases in the objective function for tmax_allsnow values greater than 0° C may indicate less sensitivity to decreases in the proportion of rain versus snow, or that rain events occur at temperatures much warmer than 0° C.

Constrained Calibration Performance

Calibrated model performance at each level of parameter fitting was measured using the Nash-Sutcliffe CE (Table 3). The uncalibrated parameters produced the poorest performance of all the levels of fitting. At this level, the best simulation results were obtained in the Animas basin with less satisfactory results in the other basins.

At the second level, calibrating the PET parameter and applying the exhaustive search procedure in the xyz methodology provided improved results in all basins. The increases in the CE were 0.26 in the Carson basin and 0.05 in the Animas and Cle Elum basins. The smaller levels of improvement in the Animas basin implies that the initial selection of climate stations in and near the basin was reasonable but that improvement in model performance is possible. A similar statement can be made for the Cle Elum basin but only after observing the results from level 3 which indicated that timing was a larger source of error than the water balance.

The fitted bias corrections, associated with gauge-catch error for snow, were 30, 0, and 10 percent for the Animas, Carson, and Cle Elum basins respectively. These values appear reasonable, with the exception of the Carson basin. As with any parameter fitting exercise, the station-set selection and bias correction may be adjusting for biases in the data as well as biases in other parameters or model conceptualizations.

Calibrating the runoff-timing parameters at level three increased the CE by 0.17 for the Cle Elum basin but only 0.05 and 0.02 for the Carson and Animas basins respectively. Calibrating the GIS Weasel estimated parameters at level four increased the CE an additional 0.05 in the Animas and Carson basins but only 0.01 in the Cle Elum basin.

The stepwise fitting provided a mixed picture of the value of the estimated parameters in each group. Improvement in model performance varied among the basins with the fitting of each group. Improvement in the Animas was about the same for each fitting step, while the meteorological parameter fitting on the Carson and timing parameter fitting on the Cle Elum provided the greatest improvement in model performance.

DISCUSSION AND CONCLUSIONS

The results presented have provided an overview of the initial methods and tools that are being integrated into a modeling framework for use in the development, testing, and application of *a priori* parameter-estimation methodologies. While limited in scope, the results raise a number of issues that need to be addressed in the continued development and enhancement of the methods and tools. These issues relate to the general categories of datasets, parameter-

Table 3. Nash-Sutcliffe coefficient of efficiency for four levels of parameter fitting.

Level	Animas	East Fork Carson	Cle Elum
1. Uncalibrated	.73	.47	.52
2. Exhaustive search xyz	.78	.73	.57
3. Optimize timing	.80	.78	.74
4. Full optimization	.85	.83	.75

estimation methods, and measures of model performance.

Dataset issues include concerns of dataset consistency, areal extent, and value. The datasets used in this study were selected because they were available for the entire United States and each was produced with a consistent methodology. This enabled the comparison of parameter estimation methods and the information content of the dataset among different regions of the United States. The value of a dataset relates to measures that include the accuracy of the data and the effect of the data on improved model performance. The value of the STATSGO soils dataset was shown to be limited in the basins tested because of the insensitivity of the model to the computed available water-holding capacity parameters. To get a more complete measure of the value of the STATSGO dataset, basins with rain as a more dominant precipitation form will need to be included in the study. Expanding the study to all regions of the United States will enable a comparable evaluation of the value of other available datasets for a range of models and process parameterizations.

Alternatively, parameters calculated using the vegetation type and density datasets had a much higher sensitivity but raised another concern that leads into the issue of appropriate parameter-estimation methodology. An attempt was made to use the forest density dataset as a surrogate for the forest cover density parameter in PRMS. However, inconsistencies in the interpretation of these two physical measures were a major source of parameter and model error.

An alternative approach to using dataset values directly in parameter computation is to first calibrate spatially distributed parameters on a typical set of basins within a region of interest. Then regression equations, relating the calibrated parameter values to values in the dataset, are developed. The resulting regression equations and original datasets are then used to estimate distributed parameters on other basins in the region (Abdulla and Lettenmaier, 1997; Xu, 1999). While the referenced examples used modeling approaches different from PRMS, the method should be applicable to a wide of variety of lumped and distributed models. One concern, however, is that fitted parameters may be biased by other sources of error, thus the value of this approach compared to other approaches needs more evaluation. It also requires a reasonable number of gauged basins with sufficient spatial variability to address the full range of related basin characteristics and parameter values.

Methods to define the distribution of precipitation and temperature are key to being able to accurately simulate distributed hydrologic processes and streamflow. While this is a problem in all regions, it is most pronounced in areas of complex and mountainous terrain. In the Animas basin, the uncalibrated xyz methodology using precipitation and temperature stations in and near the basin produced reasonable model performance. Application of the xyz exhaustive search procedure brought model performance in the Carson basin to an acceptable level and improved performance in the Animas basin further. The testing and development of the xyz methodology began in mountainous regions and has only recently begun testing in other regions of the United States. It should be applicable for temperature distribution in all climatic and physiographic regions. For precipitation distribution, it is most applicable for frontal type precipitation events that occur over an entire watershed. Modifications to the current xyz method as well as other techniques are being evaluated for use with more localized, convective-type storms.

In the Cle Elum basin the effects of the xyz methodology on model performance was masked to some degree by the errors associated with poor estimates of the runoff-timing parameters. This observation identifies two issues. One is the general lack of a regional or global dataset for geological and hydrogeological characteristics that could be used to assist in the estimation of runoff-timing parameters related to the apportioning of the surface and surface components of streamflow generation. These parameters were estimated from model application to other basins in this region and the results reflect some of the potential difficulties in transferring parameters from one basin to another.

The second issue is the question of how to best identify and measure the sources of error, such as data, parameter, and model error, and what measures are most appropriate for objectively defining parameter and model performance. The Animas and Carson model results were described above as being acceptable. The level of acceptability is typically a subjective judgment and needs to be more clearly defined in terms of what specific measures are most appropriate and what are acceptable magnitudes of those measures.

Measures of model performance are also needed to compare uncalibrated performance versus the calibrated model. Appropriate measures could be used to provide confidence limits for simulation results on ungauged basins. Such measures would also provide a consistent way to compare other methodologies and models. Defining the appropriate measures of performance is a question that still needs to be addressed.

Historically the measure most typically used for calibrating and evaluating distributed parameters has been streamflow. However, streamflow integrates the spatial variability of the process parameters being fitted. Thus it is possible to obtain a reasonable simulation for the wrong reason. A more appropriate measure of distributed parameter performance would be spatial measures related to the process being simulated. Increasing availability of remotely sensed data is now making it possible to begin to develop some independent measures of distributed parameter model performance. One such measure currently available is snow-covered area.

The ability of PRMS to adequately simulate streamflow and the spatial and temporal distribution of snow-covered area has been demonstrated in the Carson basin (Leavesley and Stannard, 1990) and in five basins adjacent to the Animas basin (Leavesley et al., 2002). A comparison of the model simulated snow-covered area with that measured by satellite, throughout the melt season, showed that the spatial and temporal distribution of snowpack accumulation and melt agreed well with the satellite data for the basins in both regions. Concurrently, simulated streamflow agreed well with the volume and timing of measured streamflow. The agreement in simulated snow-covered area and streamflow volume and timing infer a measure of confidence in the parameter estimation methods applied and in the transferability of the methods to ungauged basins. The Carson and Animas basins were selected for this study in part based on the results of these previous studies.

To address the issues raised in this study and to build on its results, the parameter-estimation methodologies will be tested and enhanced using tens of basins in a number of climatic and physiographic regions of the United States using a variety of process conceptualizations. Test basins provided by the Model Parameter Estimation Experiment (MOPEX) project (http://www.nws.noaa.gov/oh/mopex/), which is a cooperative activity of the international scientific community, will be used to expand the study to basins in other regions the world.

To facilitate this, the GIS Weasel and xyz methods will be enhanced to operate in a batch mode. User-specified recipe files in the GIS Weasel will define the delineation, characterization, and parameterization procedures to be applied to the select basins in each region. Alternative recipe files will be developed for each model and each set of parameter estimation methods and datasets to be evaluated. The Shuffle Complex Evolution Optimization algorithm (Duan et al., 1993) and the Multi-Objective COMplex Evolution algorithm (Yapo et al., 1998; Gupta et al., this volume, "Multiple Criteria Global Optimization for Watershed Model Calibration"), which is capable of solving multi-objective optimization problems, are also being incorporated in to MMS. The Monte Carlo methodology is being expanded to incorporate the Generalized Likelihood Uncertainty Estimation (GLUE) procedure (Beven and Binley, 1992; Beven and Freer, 2001; Freer et al., this volume).

This research effort is not unique. A variety of systems and tools to address the issues of parameter estimation and uncertainty analysis are being developed by other investigators using approaches that include multi-criteria optimization, sensitivity analysis, and generalized likelihood uncertainty analysis techniques (Beven and Binley, 1992; Beven and Freer, 2001; Yapo et. al., 1998; Wagener et. al., 1999; Wheater and Lees, 1999). What separates MMS from these other systems is the Open Source software system approach in which all members of the scientific community can participate in the design and development of the system framework, process modules, and analysis and support tools. The resulting toolbox will facilitate the multidisciplinary, systematic approach that is needed to 1) identify the most appropriate estimation methods for use with different models in different climatic and physiographic regions, and 2) define the robustness and reliability of these methods and their associated datasets.

Further information on MMS and the GIS Weasel can be found at:

http://wwwbrr.cr.usgs.gov/mms
http://wwwbrr.cr.usgs.gov/weasel

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